Classification and Suitability of Sensing Technologies for Activity Recognition

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Abstract

Wider availability of sensors and sensing systems has pushed research in the direction of automatic activity recognition (AR) either for medical or other personal benefits e.g. wellness or fitness monitoring. Researchers apply different AR techniques/algorithms and use a wide range of sensors to discover home activities. However, it seems that the AR algorithms are purely technology-driven rather than informing studies on the type and quality of input required. There is an expectation to over-instrument the environment or the subjects and then develop AR algorithms, where instead the problem should be approached from a different angle i.e. what sensors (type, quality and quantity) a given algorithm requires to infer particular activities with a certain confidence? This paper introduces the concept of activity recognition, its taxonomy and familiarises the reader with sub-classes of sensor-based AR. Furthermore, it presents an overview of existing health services Telecare and Telehealth solutions, and introduces the hierarchical taxonomy of human behaviour analysis tasks. This work is a result of a systematic literature review and it presents the reader with a comprehensive set of home-based activities of daily living (ADL) and sensors proven to recognise these activities. Apart from reviewing usefulness of various sensing technologies for home-based AR algorithms, it highlights the problem of technology-driven cycle of development in this area.

Keywords: activity recognition, sensors, ADL

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1. Introduction

In the last two decades sensors have become cheaper, smaller and widely available, residing at the edge of the Internet. Some such examples are wearable personal activity (PA) trackers (e.g. Fitbit, Nike+ FuelBand, etc.). However, the available commercial off-the-shelf (COTS) sensors are only capable of 'sensing' a small subset of user activities – mostly outdoor sport activities (type of activity, distance covered, time taken, etc.) and estimation of additional information such as energy expenditure (either kcal or self-crafted metrics e.g. Nike's fuel-points). However, a large part of our lives, and increasingly so in the advanced age, is spent in the home, yet very little is known about our activities and behaviour in there.

We are surrounded by a multitude of sensing devices and Mark Weiser's vision of ubiquitous computing [120] is starting to materialise in the advances made in embedded networked systems currently addressed as the Internet of Things (IoT). The significant increase in devices streaming low-level information over the Web presents many new challenges. Whilst many researchers present this as a big data challenge, we believe that many of the environments and applications will require to justify the value and process relatively small data, making this a two-faceted problem requiring to consider the highly distributed, non-interoperable, small and relatively "lonely" data. Efficient and accurate activity recognition (AR) algorithms are needed in order to make sense of this data and provide useful/actionable information and services in the human activity monitoring context. However, the task of AR is not trivial and the reality is that not all user activities are recognisable using all available sensors and algorithms. Often we simply do not know what activities people do on daily basis. Self-reporting techniques i.e. asking people to log their own activities, do not always work and there is an increasing need for automation. If sensorised systems were capable of reporting on all user activities this would enable researchers to undertake a very broad range of clinical and longitudinal studies. An analysis of a single activity (e.g. walking) in isolation is often insufficient to judge on one person's physical condition or to judge on the success of an intervention. Instead, researchers and doctors are in need to gain a complete picture/profile of a person to observe changes and relationships that arise over time.

This paper was motivated by the need to answer the question as to what are best sensor data and technologies in terms of their capability to support accurate recognition of a large set of activities of daily living (ADLs), and it is a result of a systematic literature review focused on works reporting using such technologies. It mainly focuses on *sensor-based* and not on the *vision-based* AR, however examples are also given from this field. Section 2 gives motivation for automatic activity recognition, describes the taxonomy of AR present in the literature, introduces health services, taking the example of the UK National Health Service (NHS) Telecare and Telehealth solutions, and provides an insight into subclasses of *sensor-based* AR. Section 3 introduces the hierarchical taxonomy of human behaviour analysis tasks and explains the origin of the dictionary of ADLs used in the analysis. Tasks and sub-tasks of ADLs are organised hierarchically and each category is analysed separately. The paper concludes with a discussion (Section 4) which summarises findings and highlights the problem of technology-driven AR algorithms development.

2. Background

According to the World Health Organization (WHO), between 2015 and 2050 the proportion of the world's population over 60 years will nearly double from 12% to 22% [122]. Only in the UK, in 2010 "10 million people were over 65 years old. The latest projections are for 5.5 million more elderly people in 20 years' time and the number will have nearly doubled to around 19 million by 2050" [28]. An ageing population and the increase in chronic illnesses such as diabetes, obesity, cardiovascular and neurological conditions have influenced research directing it towards sensor-based solutions. One of the medical conditions which affects a large proportion of each country's population is stroke – affecting 15 million people worldwide each year [124]. With so many elderly citizens and an ageing society, healthcare systems all over the world are at financial risk. New models of healthcare are needed, in which technology can be utilised not only to reduce the cost of care but also to assist elderly citizens' well-being and in living an independent life. NHS in England has brought to life 15 Academic Health Sciences Networks (AHSN) to mainly "deliver measurable gains in health and wellbeing" [112]. The NHS currently faces the problems of: reduced public funding, rising costs and increased demand; and sees the solution in inverting the current healthcare system towards personalised and decentralised healthcare [109]. Sensor technology is the main medium through which this patient-centric healthcare model can be accomplished.

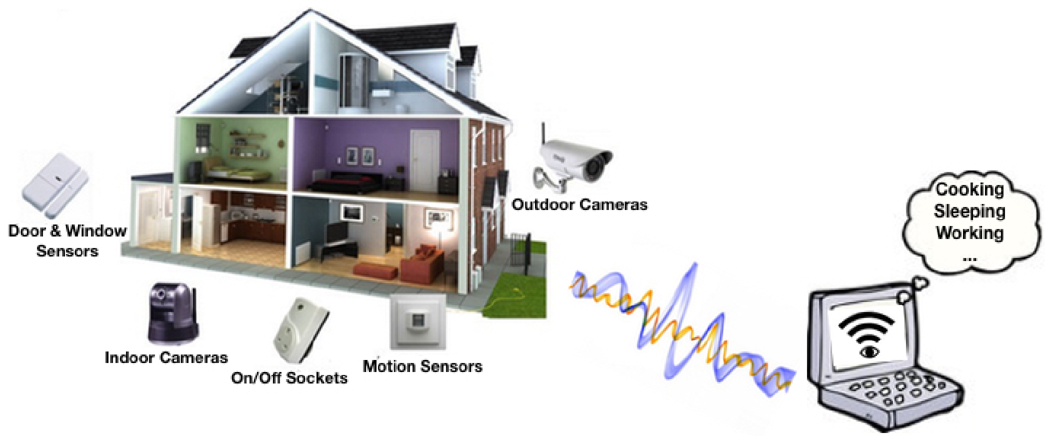

Figure 1: From Real-World to Activity Recognition via Sensors.

Adaptation of sensor technology in order to satisfy healthcare requirements raises many challenges, ranging from the selection of suitable sensors and their (user) acceptance to finding efficient and reliable AR algorithms. How to select the suitable technology? How would a clinician or a researcher know which sensor is fit for a given purpose, bearing in mind some predetermined constraints (e.g. cost, privacy constraints)?

A sensor measures a single real-world parameter/variable and turns it into an analogue or digital signal. A single measurement may be useful for simple applications (e.g. temperature monitoring in the office) and may be sufficient to discover very simple events (e.g. fire in the office), but it is often insufficient for an automated system that can infer all the activities taking place in an area of interest. Therefore, a fusion of multiple sensor readings is often needed for an activity recognition system to reconstruct what has been captured – as visualised in Fig. 1. There are multiple ways of approaching AR, described in the reminder of this section. The strength of the IoT lies in the foundations of the Internet i.e. distribution of resources, support for common naming schema/ontologies, common access strategies, and availability of computational resource to mention a few. The challenge is to locate and fuse the right pieces of (sensor) information together in order to infer activities of interest at the best quality of information possible.

2.1. Activity Recognition and Taxonomy

Activity recognition is "the process whereby an actor's behaviour and his/her situated environment are monitored and analysed to infer the undergoing activities. It comprises many different tasks, namely activity modelling, behaviour and environment monitoring, data processing and pattern recognition" [24]. There are many approaches for delivering AR which have been classified by various taxonomies – as illustrated by Fig. 2. One classification is based on the data type the AR system processes and thus there are two main classes: *vision-based AR* and *sensor-based AR* [99, 24]. *Vision-based AR* uses visual sensing devices such as camera-based surveillance systems, or most recently, RGB depth cameras designed for motion-sensing applications and games such as Asus Xtion PRO LIVE[1] or Microsoft Kinect [138]. It utilises computer vision techniques to analyse video images and extract meaning from them. Aggarwal and Ryoo [1] further classify the *vision-based* techniques into: *single-layered* approaches and *hierarchical* approaches; which are then classified further into sub- and sub-sub-categories. In computer vision, *single-layered* approaches are those that recognise activities directly based on sequence of images. *Hierarchical* approaches on the other hand, represent high-level activities by describing them in terms of a sequence of other simpler activities i.e. subevents. Thus, these *hierarchical* approaches are composed of multiple layers, making them suitable for the analysis of complex activities [1]. *Sensor-based AR* exploits sensor network technologies to measure actor's motions and their interaction with the environment. Chen and Khalil [24] further divide the *sensor-based AR* approaches into: *wearable sensor-based* and *object-based* (also called *dense sensing*). The former is achieved by attaching sensor(s) to an actor under observation – usually inertial measurement units, vital sign monitoring devices and Radio-Frequency Identification (RFID) tags or readers. On the other hand *object-based* AR is achieved by monitoring an actor's interaction with surrounding objects by either instrumenting the environment only, or by instrumenting the environment as well as the actor. This has become possible due to the miniaturisation of sensors, their low cost and low power consumption, and advancements made in the field of wireless sensor networks. There are also projects which link across these categories and analyse sensing data originating from different sensing modalities e.g. the SPHERE project [126]. The presented taxonomy is based

[1] https://www.asus.com/3D-Sensor/Xtion_PRO_LIVE/

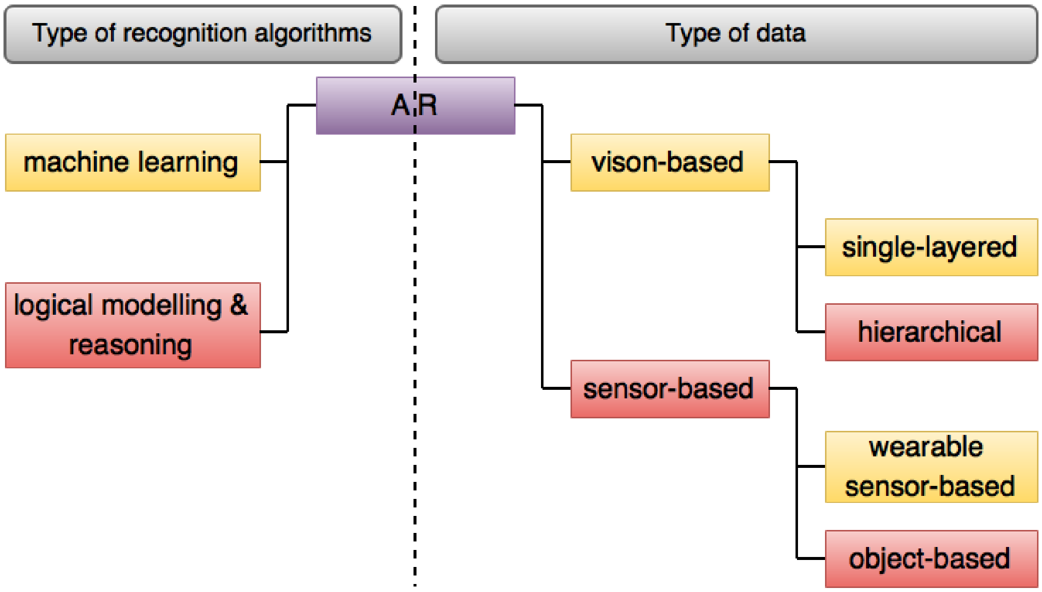

Figure 2: Activity recognition taxonomies.

on the means of perceiving the physical environment by the systems i.e. visual-based and sensor-based AR systems. Another classification is based on the type of recognition algorithms [24]: *machine learning* techniques and *logical modelling & reasoning*. Both taxonomies are valid and do not contradict each other, as one is based on the type of input and the other on the type of applied algorithms.

2.2. NHS Telecare and Telehealth Solutions

Sensor solutions are already present in the UK's NHS. These include *telecare* and *telehealth* systems. *Telecare* is simply a service which enables elderly and vulnerable individuals to live a safe and independent life in their own homes. It involves personal and/or environmental sensors in the home, which can trigger an alarm and notify a family member, friend, neighbour, nurse, etc. Examples of these can be:

- A personal alarm in the form of a wristband or a pendant, which is triggered by pressing a button[2],

[2]http://www.nhs.uk/Planners/Yourhealth/Pages/Telecare.aspx

- Motion sensors, which reduce the risk of falls by switching on lights in the house upon discovering movement[2],
- Pressure mats that can raise an alarm if a person did not make it back to bed during nighttime[2],
- Portable medicine dispensers prompting patients to take their medication (ringing/flashing alarm reminder)[3],
- Epilepsy sensors[3], etc.

Another class of technologies which can be used at home are *telehealth* solutions. These are for remote health monitoring, which reduce health service's costs by cutting down on the number of unnecessary face-to-face interactions between patients and healthcare professionals (HCPs). With the aid of *telehealth* technologies, home residents can monitor their basic health parameters such as: blood pressure, blood glucose levels, temperature, weight, etc. Users are trained on how to take measurements of their vital health sings, which are then automatically transmitted to the relevant HCP. In this way HCPs provide an indirect care to their patients, who in turn do not have to travel to the hospital/GP surgeries. While reducing care costs, these technological solutions have "potential to make significant health improvements and quality of life impacts for people with a high dependency on the NHS, local GPs, social services and local hospital"[3]. Both of these classes of technologies were estimated in 2012 to save UK's NHS 1.2 billion GBP over 5 years period[4]. Moreover, they give peace of mind to patients' relatives and prevent families from placing their beloved into care homes. However, these technologies are not ideal as they either require user input (how can somebody already unconscious press a button?) or are based on very simplified models of behaviour (what if somebody wakes up in the middle of the night and decides to watch TV and falls asleep in front of it?). Moreover, would a person suffering from multiple conditions or a complex condition (e.g. somebody with epilepsy or post stroke) require multiple systems/sensors (e.g. having to wear multiple pendants/bracelets) to account

[3] `http://3millionlives.co.uk/about-telehealth-and-telecare#what_is_telecare?`

[4] https://www.gov.uk/government/news/telehealth-and-telecare-could-save-nhs-1-2-billion

for all the possible dangers? Is this safe and acceptable from the user perspective? More complete solutions, which do not require user intervention (e.g. pressing a button), are needed to provide a truly safe environment for independent, technology-assisted living.

2.3. Wearable Sensor-based AR

As various studies have shown [87, 61, 88, 9, 52], body worn sensors can be very effective for the purpose of activity recognition, however they are not always acceptable from the subject's perspective. Moreover, human behaviour is often influenced by the presence of other humans or by the consciousness of being watched – of which wearable sensors, if not seamlessly integrated, can be a strong reminder. Secondly, as pointed out in [24], "many activities in real world situations involve complex physical motions and complex interactions with the environment. Sensor observations from wearable sensors alone may not be able to differentiate activities involving simple physical movements, e.g. making tea and making coffee". Therefore, on one hand wearable sensor-based solutions achieve high activity recognition rates:

- Bao and Intille, using decision tree classifiers, achieved recognition rates of between 80% 95% for 20 activities, with the overall recognition rate of 84.26% [9],

- Parkka et al. conducted a study in which 7 activities (Lie, Row, ExtBike, Sit/Stand, Run, Nordic walk and Walk) were classified using three different approaches: custom decision tree classifier (total classification accuracy of 82%), automatically generated decision tree (86%) and artificial neural network (82%) [87].

On the other hand they violate basic principles of ubiquitous computing i.e. calmness – technology "which informs but doesn't demand our focus or attention" [121] – and comfort.

However, with the progress in miniaturisation of technology, wearable sensors became small and attractive, offering many interesting features. Mainly due to the offered features, people decide to wear physical activity (PA) trackers. Successful marketing of these products, offering social media integration and concepts such as reward badges (e.g. Fitbit), introduced a social dimension to it. Therefore, many users have decided to adopt technology that tracks some of their moves irrespective of potential privacy implications. Whether it's a watch-like sensor worn on a wrist or AA-battery size

Fitbit worn on a wrist or belt, people agree to put these devices on every day in exchange for the information/activities they record. The major downside of these devices is the limited set of features they provide: number of steps taken, distance walked, energy expenditure (kcal) and sleep duration. Moreover, the quality of information they provide is usually not satisfactory, as revealed for example by the following studies: Fitbit Ultra[5] is found to have fair to good accuracy in identifying steeping activity for stroke and TBI patients [42] with an Intraclass Correlation Coefficient (ICC) of 0.73, and for healthy subjects agreement was above 95% [68]. The same study found Nike+ Fuelband[6] to have an ICC of 0.2. In this study the ground-truth for comparison was collected with a video camera (manual counting of steps) and was also used to validate the StepWatch Activity Monitor (SAM)[7] which is a gold standard widely used in clinical settings (ICC=0.97). Another study [39] compared 7 personal activity trackers with two research grade accelerometers and resulted in similar conclusion but with higher ICC scores. However, all 7 devices scored very poorly for energy expenditure (kcal) estimation with a highest ICC score of 0.57. Study [59] provided higher agreement scores and found three devices to be within a 10% equivalence zone around the indirect colorimetry estimate.

Market for PA trackers is now fairly mature and starts moving in the direction of smart watches. There are many smart watches on the market which are not stand-alone devices but rather interface the user with their smart-phone in a convenient way e.g. Apple Watch[8] or Android Wear[9]. The advantage of this type of technology is that people wear watches anyway and hence are not asked to put on yet another device. Moreover, placement of the watch allows for relatively accurate measurements of pulse and arm movements. On the downside, battery life of smart-watches often matches the short lifetime of a smart-phone's battery. In addition, assessment of movement from a wrist-based accelerometer results in overestimates. Another competitor in the market of commercial products are software apps for Android and iOS platforms using their built-in accelerometers. However,

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[5] `http://help.fitbit.com/articles/en_US/Help_article/About-the-Fitbit-Ultra`

[6] `http://store.nike.com/gb/en_gb/pw/mens-nike-fuelband-se/7puZd4d`

[7] `www.orthocareinnovations.com/uploads/files/Grants\%20Guidance.doc`

[8] `http://www.apple.com/uk/watch/`

[9] `http://www.android.com/wear/`

studies such as [46] revealed rather poor validity of an iPhone Moves app with an error rate of 27.28%.

2.4. Object-based AR

Object-based AR, even though nowadays financially affordable, is very laborious in terms of setting up the environment. Labelling of everyday life objects, such as mugs, boxes with tea, coffee, milk, etc.; imposes a huge overhead and workload to the system administrator, when one of the most desirable feature of AR sensor-based systems is their low maintenance factor and ability to operate unsupervised. Moreover, if there are many subjects in the monitored environment, it becomes hard to infer who the subject of the action was. The authors of [53] use Dynamic Bayesian Network (DBN) framework for AR from interactions with objects. In their setup, a nurse performs a drip injection procedure and the purpose of the system is to prevent the cause of medical accidents and incidents. Again, this is an example of how intrusive the technology can be made by researchers. In their lab setup, the nurse had an RFID reader attached to her hand and all the objects she interacted with were tagged with RFID tags – some of them carried multiple tags to allow for precise detection of interaction. In [67] hybrid discriminative/generative approach with hidden Markov model (HMM) is used for object-based AR. Authors of this work however, did not attach sensors to various objects, but prototyped a wristband type device consisting of: camera, microphone, accelerometer, illuminometer and digital compass. Moreover, they claim that these sensors can be embedded into a wristwatch, which would solve the problem of users having to wear uncomfortable sensors. The basis for AR recognition is formed by the visual feature extraction. The biggest downside of this approach (and of other vision-based approaches) is the use of camera, which invades user privacy and drains battery very quickly as images are continuously sent over the air to the host PC. As with every machine-learning approach, this HMM approach to AR requires training data, which has to be "acquired in each user's environment because these sensor data are environment dependent" [67]. Moreover, the training data needs to be annotated, which is a tedious task. Therefore, these AR systems usually do not perform well straight out of the laboratory. Training data is hard to acquire and hence these solutions are not very scalable.

The Ambient Kitchen in the Culture Lab, Newcastle University is yet another example of dense sensing. The sensor infrastructure (made up of 3-axis accelerometers) is integrated into a number of kitchen utensils: knives, pots and lids, frying pans, a peeler, a grater, a measuring cup, a sieve, a spoon, a spatula, a ladle, a whisk and a chopping board [118]. Despite the fact that such setup provides an accurate and fine-grained level of information, deployment of such systems in people homes is rather laborious and expensive. Moreover, in multi-resident environments some form of localisation is needed to differentiate between different occupants.

3. Suitability of Sensing Technologies for ADL

3.1. Hierarchical Taxonomy of Human Behaviour Analysis Tasks

The adopted taxonomy of Human Behaviour Analysis (HBA) tasks builds up on the work presented in [22]. It is a result of a collaborative effort between researchers working on the SPHERE [126] project. Fig. 3 represents this classification in the form of a pyramid with the following HBA tasks: physiology, pose, motion, action, activity and behaviour. The time duration and the complexity of HBA tasks grow with each pyramid level. In this taxonomy, at the bottom sits physiology. Physiological signals such as EEG, ECG, blood pressure and temperature are typically measured in millisecond intervals. Next in the hierarchy is pose, also known as posture and it refers to the arrangement of every part of the body. At the next level is motion, which is the movement of the entire body or part of the body, not necessarily with intent nor a complete action. "At the action level, human motion is not only detected, but also recognised in order to establish what a person is doing or with which objects the person is interacting" [22]. A sequence of actions performed in some order can be classified as activities. Activities are usually intentional, even though humans can perform them without much attention or thought and have duration of seconds, minutes or even hours. Examples of these can be: watching TV, working or eating. At the top of the pyramid sits behaviour i.e. how people do an activity relative to their pattern over time or norm across some population.

3.2. Dictionary of Activities of Daily Living

The dictionary of activities of daily living (ADL) has been compiled during the SPHERE project meetings between researchers from Bristol, Reading and Southampton universities and clinicians. The result of this collaborative effort has been extended for completeness mainly with activities found in

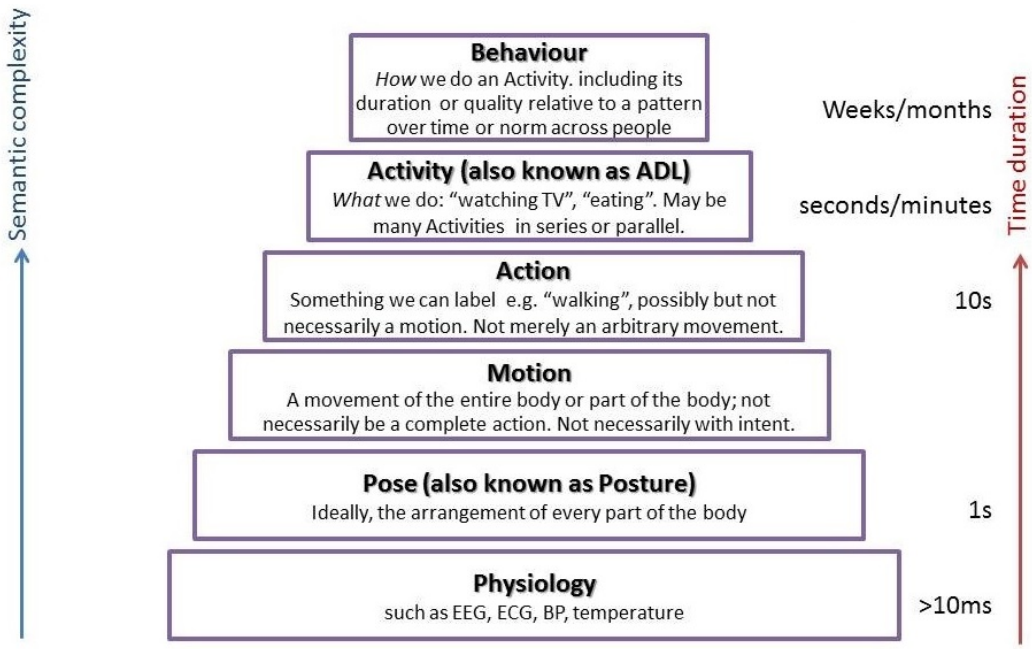

Figure 3: SPHERE Hierarchical Taxonomy for People

the Compendium of Physical Activities[10]. It does not capture all possible tasks which can be performed in the home environment but focuses on the most important ones or rather most relevant in the clinical context. The dictionary of ADLs has been hierarchically organised into tasks and their sub-tasks, which are classified into one of the HBA tasks captured in Fig. 3. No model is fully complete and hence the intention is to extend this model whenever necessary.

3.3. Suitability of Sensing Technologies for Home AR

Tables presented in this section identify which sensors are capable of capturing/sensing information required to recognise each of the sub-tasks. They have been colour-coded to indicate how achievable AR of a particular ADL is with the given sensor. Therefore, green colour in the table marks studies which have successfully recognised a particular home activity. Yellow denotes likely or achievable with the named technology. Orange means that we

[10]https://sites.google.com/site/compendiumofphysicalactivities/Activity-Categories/home-activity

anticipate that AR can be achieved for the particular activity. Red marks difficult or impossible with existing technology. The list of all abbreviations and terms used in this table together with their meaning are shown in Table 1. Numbers in parenthesis next to sub-task names refer to the SPHERE hierarchical taxonomy in Fig. 3. Physiology, pose, motion, action, activity and behaviour have been coded with numbers -1, 0, 1, 2, 3 and 4 respectively. The last column represents anticipated solutions, which is more of an informed guide on the types of technology suitable for the recognition of a particular activity. Moreover, it is worth adding that cameras or Kinect sensors do not imply recording of audio but only deal with video footages. Since using cameras in some locations (e.g. bathrooms) raises ethical and privacy concerns, certain activities in the 'Video' column are marked as 'privacy issues'. Interestingly, some studies revealed that people find audio recording more intrusive than video [81].

Studies included in the analysis range from lab-based to free-living scenarios and focus on home-bound ADLs and not on outdoor activities. Some studies over-instrumented test subjects with far too many sensors [129], which might be acceptable in short-term lab experiments but not in free-living environments. Research tools/sensors are useful to prove a given concept but to be applicable (and ubiquitous) to people's lives they need to take different shape, more compelling and comfortable to the user.

PA trackers (including smart-watches) and smart-phone apps, although very popular, have been excluded in this analysis, since they only provide a very limited set of information e.g. number of steps taken, distance walked, energy expenditure (kcal) and sleep duration. Moreover, as documented by numerous studies and as discussed in Section 2.3, the quality of information is usually not satisfactory. It is anticipated that as technology develops both PA trackers and software apps for smart-phones will become more accurate.

The activity recognition confidence factors have been purposely left out, as these are often subjective and/or relative to the specific models of sensors (and not their general type) used in the study. These figures wouldn't be truly representative of the current state-of-the-art as better quality sensors enter the market every day. For example, if some activity was recognisable with a Kinect sensor (with relatively high precision and recall) it is likely that with the new Kinect 2 sensor the precision and recall would be even greater. Moreover, AR algorithms/methods used in the reviewed studies have also been left out as the review was carried out at the hardware level (sensors) and not at the algorithmic level in order to identify which sensors are capable

Table 1: List of abbreviations and terms

Term	Meaning
A	Accelerometer (A^U, A^B, A^T, A^4 – uni-, bi-, tri-, four-axial)
AG	Accelerometer and Gyroscope
AGC	Accelerometer, Gyroscope and Compass
ALT	Altimeter
BAR	Barometric pressure sensor
C	Compass
Dense sensing	Concept in which all objects the subject is likely to interact with are equipped with tags capable of wirelessly reporting the use of that object (usually a simple motion sensor)
DFAR	Device-Free radio-based Activity Recognition system
ECM	Electricity Monitoring e.g. [32]
EMG	Electromyogram
eWatch	Dual-axes accel., light, temperature sensor and microphone
G	Gyroscope
ICC	Intelligent Calorie Counter (2xmonolithic IC accelerometers + piezoresistive pressure sensor)
Intelligent Floors	Relates to the concept of using tactile sensor arrays embedded in the house flooring e.g.[108],[78]
Kin	Microsoft's Kinect motion sensing device
MSP	Mobile Sensing Platform
MTx	Mote consisting of accelerometer, gyroscope and magnetometer
MTx 3-DOF	Mote consisting of A^T, G^T and tri-axial magnetometer
PROX	Proximity sensors
RTLS	Real Time Location System
SF_APPS	Apps usage monitoring (software) e.g. PC, tablet, smart-phone
SP	Smart Phone
SpO_2	Pulse Oximetry sensor
W-ECG	Wearable Electrocardiogram
WISP	Wireless Identification and Sensing Platform (UHF RFID + A)

of recognising a given activity. Knowledge captured in this form identifies the utility of various sensors and can inform answers to the following questions:

- Which sensors are capable of recognising the most activities?
- Which sensors are fit for the recognition of a particular activity?
- What are the alternatives for recognising a particular activity under imposed restrictions (e.g. camera cannot be used for privacy reasons)?

- Which activities are difficult to recognise or have not been targeted by researchers yet?

Most importantly, the analysis presented here can be used by non-technical users, such as clinicians to understand the capabilities of various technologies, and for example, make an informed decision on sensor selection for their own studies. Another group of users who would benefit from such information are doctors. In the future, when obstacles such as sensors interoperability issues (plug&play ability of COTS sensors is achieved) are overcome, we envisage doctors/clinical consultants to be able to 'prescribe' sensors to individual users based on their needs, while taking into account their preferences and other selection criteria (such as price, privacy restrictions, obtrusiveness, etc.). Since the current healthcare model is unsustainable with the ageing society, doctors or some technically oriented consultants will need to know what sensors can deliver the information they are after.

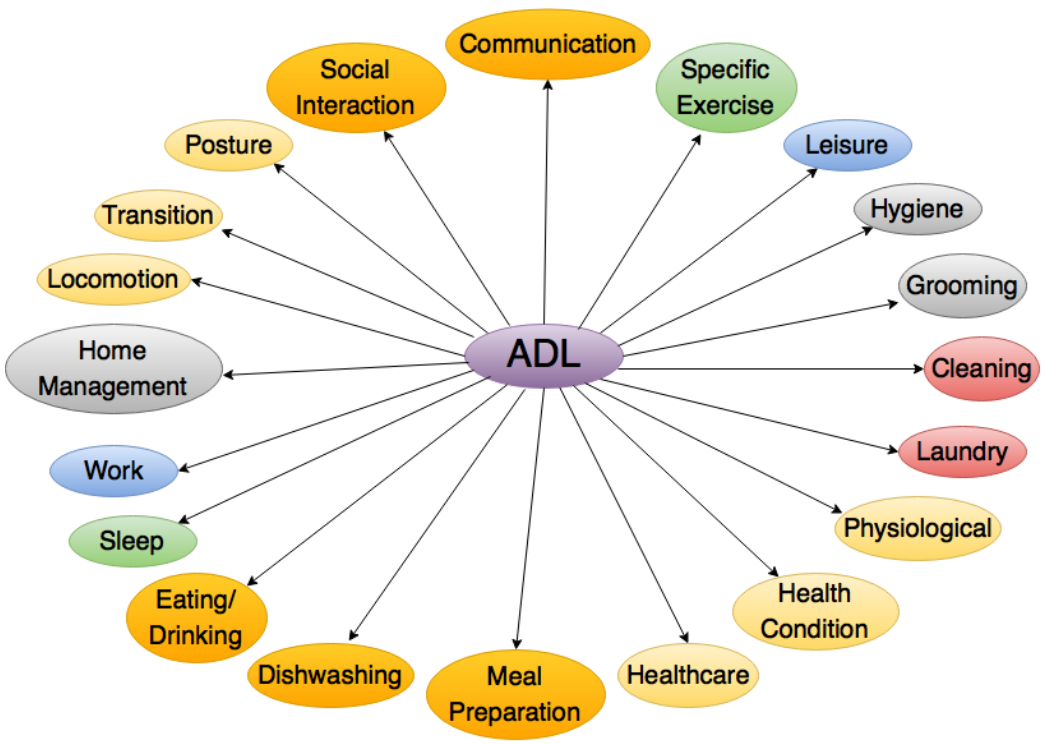

Figure 4: Categories of ADL.

The following sub-sections provide an overview of sensing technologies suitable for the recognition of activities which are sub-tasks of categories found in Fig. 4. Sub-tasks of *Locomotion, Transitions and Posture* in Section 3.3.1 all relate to basic human movement and are often recognised using inertial measurement units e.g. accelerometers and gyroscopes. On the other hand, activities found under *Social Interaction* and *Communication* tasks (Section 3.3.2) tend to be recognised via use of EMG sensors which can detect person's speech. These sub-tasks are of particular interest to clinicians, especially in the context of people living on their own and those with mental illnesses and disorders such as depression. Similarly to these, sub-tasks of *Leisure* in Section 3.3.3 are good indicators of person's mood and levels of interaction with ambient space. Recognition of activities listed under *A Specific Exercise* in Section 3.3.4 is important not only for subjects undergoing physical rehabilitation but also for healthy individuals – as a way of monitoring their general fitness. Recently, the focus of researchers has shifted towards assessing quality of movement, as incorrectly performed exercises can do more harm than good. Sub-tasks of *Hygiene, Grooming, Cleaning and Laundry* presented in Sections 3.3.5-3.3.6 have not received much attention, yet are very important for AAL scenarios as they have direct influence on subject's health e.g. living in an untidy environment or poor hygiene. From the technological point of view, recognition of sub-tasks listed in Section 3.3.7 i.e. *Physiological, Health Condition and Healthcare*, is challenging as it involves sophisticated sensors which can be intrusive and power-hungry. Nevertheless, these sub-tasks e.g. *Breathing* or *Sweating* are highly indicative of subject's health and are of great importance to AAL systems, which are enabled to act pro-actively when vital signs become worrying. Activities classified under *Meal prep., Dishwashing, Eating and Drinking* tasks in Section 3.3.8 involve complex motions and tend to be recognisable in heavily instrumented environments and via use of body-worn accelerometers. The final sub-tasks analysed in this article are those categorised under *Home Management, Sleep and Work*. While the former tasks are of less importance, *Sleep and Work* are important factors in anybody's life.

3.3.1. Locomotion, Transitions and Posture

Sub-tasks of *Locomotion, Transitions and Posture* is the most researched area of ADLs and hence Table 2 does not include anticipated solutions. Since these activities are related to an individual's movement, accelerometers (mostly tri-axial) are the most popular means for collecting required information. A fair proportion of studies still over-instrument subjects with far too many sensors despite strong evidence that one tri-axial accelerometer is sufficient. In Table 2 some work did not report accurately on the measured sub-tasks. In situations where target activities such as running were not explicitly defined [113, 131] it was assumed that authors meant *Running* and not *Running(treadmill)* (found in Table 5) since involvement of a treadmill has not been mentioned. Although the two running categories relate to the same concept, it is worth noting that running on a treadmill is different from free running due to the treadmill setting the pace – as opposed to self-selected pace. In cases where researchers only measured one-way transitions e.g. sitting down [119], the study has been included in the table under bi-directional sub-tasks, in this case *Sit to Stand, Stand to Sit*.

Table 2: Locomotion, Transitions and Posture Sub-tasks

Sub-task	On-body (accelerometer)	Other Sensors & Software	Video
Movement(1)	3xA^T[25];A^T[74],[25]; 2xA^B[66]; 4xA^U[20], 5xA^U[21]	RFID[125](arm); W-ECG[89](arm); SP[135]	Kin, Cam
Walking (2)	A^T[37],[110],[100],[85],[74],[56],[130], [104],[2],[45],[98],[103],[60],[47],[131], [119],[31],[70]; 2xA^T[71]; A^B[107],[97]; 5xA^B[69],[9]; A^U[93]; 3xA^U[117],[10]; 4xA^U[40]; 5xA^U[21]	active/passive DFAR[105]; eWatch[76],[77]; W-ECG[89]; 7xMicaZ(A^B)[128]; A^T+G[58]; SP's accelerometer[135],[51],[14]; ICC[84]; tri-axial MTx[134]; A^B + ambient sensors[116]; A^B+G[80]; A^B+G+C[61]; MSP[26]; sEMG+8xA^T[102]; A^T+SpO_2[113]	Cam[41]; Cam+ 2xA^T[111]
Running(2)	A^T[131],[110],[119],[31]	eWatch[76],[77]; A^T+SpO_2[113]	Cam[41]
Jumping(2)	A^T[119],[31]	TelosB[43]; A^T+SpO_2[113]; 5xMTx 3-DOF[3]	
Stairs(2)	A^T[104],[110],[85],[98],[103],[60],[47]; 2xA^T[71]; A^B[107],[97]; 5xA^B[69],[9]; 3xA^U[117];4xA^U[20];5xA^U[21]	W-ECG[89]; 7xMicaZ(A^B)[128]; A^T+G[58]; ICC[84]; 5xMTx 3-DOF[3]	
Using Elevator(3)		ECM[32]; MSP[26]; 5xMTx 3-DOF[3]	

Walk Through Doors(2)		PIR[123], Break beam[36]	
Leaving the House(2)		RFID[125]	
Sit to Stand, Stand to Sit(2)	A^T[13],[100],[62],[74],[56],[130],[2],[69],[47],[37],[119]; G[79]; 3xA^U[10]	WISP[96];TelosB[43]; sEMG+8xA^T[102]; A^B+G[80]	
Sit to Lie, Lie to Sit(2)	A^T[74],[100],[56],[130]	TelosB[43]; sEMG+8xA^T[102]	
Stand to Lie, Lie to Stand(2)	A^T[2],[47]		
Standing(0)	A^T[74],[100],[110],[62],[130],[2],[45],[98],[60],[47],[131],[119],[31],[70]; 9xA^T[129]; multiple A^T[44]; A^B[107],[97]; 2xA^B[66],[30]; 3xA^B[132]; 5xA^B[69],[9]; 2xA^U[6];3xA^U[117];4xA^U[20][40], 5xA^U[21];	active/passive DFAR[105]; eWatch[76],[77]; 7xMicaZ(A^B)[128]; SP[136],[135]; WISP[96]; MTx[134]; A^B+G[80]; A^B+Ambient Sensors[116]; MSP[26]; A^T+SpO_2[113]; 5xMTx 3-DOF[3]	Kin[8]; Cam[29],[54],[75]; grey Cam[49]; Cam+ 2xA^T[111]
Sitting(0)	A^T[74],[100],[110],[62],[130],[2],[45],[60],[47],[131],[31],[70]; 9xA^T[129]; A^B[107],[97]; 2xA^B[66],[30]; 3xA^B[132]; 5xA^B[69],[9]; 2xA^U[6];3xA^U[117];4xA^U[20][40], 5xA^U[21]	eWatch[76],[77]; W-ECG[89]; 7xMicaZ(A^B)[128]; SP[136],[135]; MTx[134]; A^B+G[80]; A^B+Ambient Sensors[116]; MSP[26]; sEMG+8xA^T[102]; A^T+SpO_2[113]; 5xMTx 3-DOF[3]	Kin[8],[90]; Cam[29],[54],[75],[41]; grey Cam[49]; Cam+ 2xA^T[111]
Lying(0)	A^T[37],[100],[62],[74],[56],[130],[2],[45],[60],[47],[31]; multiple A^T[44]; 2xA^B[66],[30]; 3xA^B[132]; 5xA^B[69],[9]; 2xA^U[6];3xA^U[117]; 4xA^U[20][40]; 5xA^U[21];	active/passive DFAR[105]; 7xMicaZ(A^B)[128]; SP[136],[135]; WISP[96]; MTx[134]; A^B+G[80]; A^T+SpO_2[113]; 5xMTx 3-DOF[3]	Kin[90]; Cam[29],[54],[75],[41]; grey Cam[49]

Evidence found in the literature suggest that for the recognition of all the activities presented in the above table, apart from *Using Elevator, Walk*

Through Doors and Leaving the House, a single tri-axial accelerometer is sufficient. The main advantage of such wearable technology is the fact that it is widely available and relatively cheap. Accelerometers have already found their way into smart-phones and smart-watches. The fast-growing market of activity trackers provides evidence for high acceptability of such unobtrusive wrist-worn devices. Their main drawback is usually a short battery life, although some projects report their accelerometers to run for months on a single coin-cell battery [38]. Other solutions in this space, such as instrumenting subjects with multiple accelerometers or other devices, are more suited for lab settings rather than for AAL spaces.

3.3.2. Social Interaction and Communication

Since discovery of sub-tasks of *Social Interaction* and *Communication* presented in Table 3 involves monitoring surrounding environment, accelerometers are not suited for this. Recognition of various sub-tasks of *Social Interaction* requires either audio (body-worn or ambient) or EMG sensors around subject's neck and some means of localisation. Knowledge of subject's talking/silence and his location in relation to other people allow to differentiate between verbal and non-verbal interactions. Sub-tasks of *Communication* are harder to address since nowadays people communicate in many different ways (*SMS, Social Media, Email, etc.*) via many different media e.g. smart-phone, tablet, PC, smart-TV. Since all these devices are programmable, AR can be achieved via appropriate software applications. However, doing so (and also using video recognition for this purpose) is very intrusive and disrespectful of user privacy.

Table 3: Social Interaction and Communication Sub-tasks

Sub-task	On-body accel.	Other Sensors & Software	Video	Anticipated solutions
Verbal Activity with Nobody Present(3)		EMG sensor around neck[48] + indoor localisation	+ audio feed	Indoor localisation + audio
Verbal Interaction with Another (present)(3)		EMG sensor around neck[48] + indoor localisation	+ audio feed	Indoor loc. + audio

Non-Verbal Interaction with Another (present)(3)		EMG sensor around neck[48] + indoor localisation	+ audio feed	Indoor loc. + audio
Receive Visitors(3)				Audio, intelligent floors, indoor localisation
Phone (voice)(3)		Dense sensing[92]; ECM[32]; WISP[19]	Web cams[63]	Audio, SF_APPS
SMS(3)			High res. cam	SF_APPS
Email(3)			High res. cam	SF_APPS, IP monitoring
Social Media (fb, twitter, IM, etc.)(3)			High res. cam	SF_APPS, IP monitoring
Video Calling (Skype, Hangouts)(3)			High res. cam + audio	SF_APPS, IP monitoring

Recognition of *Social Interaction* and *Communication* sub-tasks is difficult to achieve with a single sensor. In our view, only vision-based approaches have potential to recognise all of these activities, yet for some may require audio feeds. Video devices have advantage over other sensors (e.g. EMG sensors) in the sense that they do not have to be worn by the subject. On the other hand, the monitored environment has to be heavily instrumented in order to provide a good coverage area. However, for sub-tasks of *Communication*, software apps form a good alternative to video sensors. Since most of the communication media are programmable, applications can be written for these in order to monitor speech/payloads, duration, involved parties and other attributes. However, both video and software applications are invasive of user privacy and may not be acceptable by some users.

3.3.3. Leisure

Activity recognition of *Leisure* sub-tasks is not heavily addressed by researchers probably due to the fact that these are non-functional activities and are perceived to have very little application value. Many AR studies are done in the context of healthcare and hence tend to focus on functional activities and not leisure. However, recognition of sub-tasks listed in Table 4 can be a good indicator of person's mood and habits. Maintaining a good balance between work and leisure is very important and hence automatic recognition of these sub-tasks is important for studies related to mood and mental health conditions.

Table 4: Leisure Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Playing with Pets(3)				A, PROX (worn by pets and ppl)
Playing Games (console, PC, cards, board)(3)		Dense sensing[92]; ECM[32]		A
Playing with Children(3)				A, PROX, audio
Watching TV(3)	5xA^B[9]	Dense sensing[92]; ECM[32]; WISP[19]	Web cams[63]	audio
Reading(3)	5xA^B[9]	Dense sensing[92]; [19]	Web cams[63]	A + audio
Listening to Music(3)		Dense sensing[92]; ECM[32]		Audio, SF_APPS
Dancing(3)			+ audio	Intelligent floors, A+audio
Playing Music (guitar, drums, etc.)(3)				A+audio, dense sensing
Meditating(3)				A+audio
Knitting/ Sewing(3)				Dense sensing, A
Browsing Internet(3)			High res. cam	SF_APPS; IP monitoring

Since sub-tasks classified under *Leisure* e.g. *Playing with Pets, Playing Games, Playing with Children* involve complex motions, they are difficult to recognise with the aid of body-worn sensors. For the detection of these three activities, video, accelerometer and proximity sensors are anticipated to be the suitable technologies. Activities which involve interaction with particular objects e.g. *Watching TV, Reading, Listening to Music, Playing Music, Knitting/Sewing* can be addressed by dense sensing technologies. However, the biggest drawback of such approaches is the large number of sensors required to be deployed by attaching them to objects of interest. Active RFID technology can be small and hence embeddable into objects of everyday use, yet requires some infrastructure and is difficult to maintain. Is it feasible to label every single book in the house with a sensor? To date, recognition of *Leisure* sub-tasks has not been very well addressed by the research community.

3.3.4. A Specific Exercise

A Specific Exercise (indoor) category only represents a snapshot of home exercises since a comprehensive review of sensors capable of supporting all indoor workouts would constitute a very lengthy review. Specific exercises are not activities people do without paying much attention to – as this is the case with many ADLs – and hence receive only limited attention from researchers. However, with increasing access to sensing technologies, clinicians are more and more interested not in the amount (patients can easily report on it themselves) but in the quality of exercises/movement. Incorrectly performed exercise can do more damage than good and having technology (and not physiotherapists) to supervise patients brings huge savings to healthcare providers.

Table 5: A Specific Exercise Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Rowing(3)	A^T[37]	ECM[32]	Cam	Dense sensing
Cycling (3)	A^T[37],[70]; 5xA^B[9]; 5xA^U[21]; 4xA^U[40]; 3xA^U[117];	A^B+Ambient Sensors[116]; SP[14]; 5xMTx 3-DOF[3]	Cam	Dense sensing
Sit Ups (3)	A^T[98]		Cam	A
Running (treadmill) (3)	A^T[60],[70],[85]; 5xA^B[9]; A^B[97]; 5xA^U[21];	A^B+Ambient Sensors[116]; SP[14]; 5xMTx 3-DOF[3]	Cam[41]	Dense sensing

Strength Training (3)	5xA^B[9]			Dense sensing
Bending (3)	A^T[31],[100];9xA^T[129]		Cam[54],[75]; grey cam[49]	A
Stretching (2)	5xA^B[9]		Cam+2xA^T[111]	Intelligent floors, A, G

As with *Locomotion, Transitions and Posture*, accelerometers are the leading technology in observing and identifying *A Specific Exercise* sub-tasks – as represented in Table 5. Often a single tri-axial accelerometer is sufficient, which is highly acceptable from the user point of view. Alternatively, since each of these exercises involves well-defined motions and often specific exercise equipment, vision-based approaches are expected to be capable of detecting these. Also dense sensing is seen as an anticipated solution for exercises which involve equipment and for other exercises which do not, accelerometers are the only alternative.

3.3.5. Hygiene and Grooming

This category of ADLs has not been comprehensively addressed to date. Similarly to *Social Interaction and Communication*, monitoring of sub-tasks listed in Table 6 is quite intrusive since *Hygiene and Grooming* activities usually take place in bathrooms and bedrooms. Although not yet popular, AR of these sub-tasks is very important for ensuring safe and hygienic independent living.

Table 6: Hygiene and Grooming Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Bathing/ Showering(3)		Dense sensing[92]; ECM[12]	Privacy issues	Water metering, water contact sensors
Brushing Teeth(3)	A^T[98], A^T[131]; 5xA^B[9]	Dense sensing[92]; WISP[19]; MSP[26]; sEMG+8xA^T[102]	Privacy issues	Audio + RTLS, water metering, water contact
Washing Hands(3)			Privacy issues	Dense sensing (soap dispenser or taps), water metering, audio, A, water contact

Washing Face(3)			Privacy issues	Dense sensing (soap dispenser, face-wash), water metering, water contact
Combing/ Brushing Hair (3)		sEMG+8xA^T[102]	Privacy issues	Dense sensing, A, audio
Cutting Nails(3)			Privacy issues	Audio, A
Make-up(3)			Privacy issues	A
Dressing(3)		sEMG+8xA^T[102]	Privacy issues	A, dense sensing, PROX

Due to privacy issues, video-based solutions are not appropriate yet are capable of recognising these sub-tasks. Accelerometers or other single-sensor solutions are also not frequently present in Table 6. It is anticipated that heavily instrumented AAL spaces which incorporate water sensors, dense sensing and an accelerometer worn by the subject can report on the whole range of *Hygiene and Grooming* sub-tasks.

3.3.6. Cleaning and Laundry

This is yet another category of ADLs which has not received much attention. Similarly to *Hygiene and Grooming*, sub-tasks listed in Table 7 are important in independent living. They are also a good indicator of person's physical abilities. AR of these sub-tasks is non-trivial, since individuals perform these activities in different ways and using different tools.

Table 7: Cleaning and Laundry Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Sweeping(3)			Cam+2xA^T[111]	Dense sensing, A
Vacuuming (3)	A^T[98],[131],[85]; 5xA^B[9]; A^U[93]		Cam+2xA^T[111]	Dense sensing, A
Mopping(3)				Dense sensing, A
Cleaning Windows(3)		WISP[19]		A

Polishing Floors(3)				Dense sensing, A
Dusting/ Polishing Furnitures(3)			Web cams[63]	A
Taking Trash Out(3)				Dense sensing, PROX, RTLS+A
Making Bed(3)				Dense sensing, A
Changing Linen(3)				Dense sensing, A
Laundry(3)	A^T[85]	Dense sensing (RFID)[92]		PROX, ECM, audio
Fold or Hang Clothes(3)	5xA^B[9]			A
Putting Away Clothes(3)				A, dense sensing (wardrobes)
Ironing(3)		ECM[32]	Web cams[63]	Dense sensing (iron, ironing board), A

Except of *Vacuuming, Laundry and Fold or Hang Clothes* sub-tasks, accelerometers are not the main medium through which *Cleaning and Laundry* activities are recognised. Again this subset of ADLs has not received much attention. For activities which involve subject's interaction with electrical appliances, electricity monitoring constitutes a good solution. For the recognition of activities which do not involve electrical appliances, yet involve interaction with other objects e.g. cleaning detergents, brush, mop, etc. dense sensing is a suitable approach. Finally, accelerometers have have been reported to detect only few *Cleaning and Laundry* sub-tasks.

3.3.7. Physiological, Health Condition and Healthcare

The recognition of ADLs presented in Table 8 is very challenging since it involves quite intrusive sensors. Especially monitoring of physiological signals is difficult and imposes many challenges such as battery life of sensors and their placement. Sensors used for this purpose are not re-usable and only serve one purpose e.g. glucometer sensor. Therefore, in order to monitor all physiological signs one would need to be instrumented with a countless number of sensors. From the clinical point of view, continuous monitoring of physiological signs is crucial, yet not achievable on a long-term unobtrusive basis in independent living. A very well addressed sub-task of *Health Condition* is the fall detection in which accelerometers are seen as the suitable technology.

Table 8: Physiological, Health Condition and Healthcare Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Breathing (-1)		Airflow sensor[48]; EMG sensor on chest[48]	Kin[106], Cam[86]	Audio, A, air quality (CO_2)
ECG(-1)		Intelligent garments with integrated textile electrodes[27]; ECG sensor[48]	Cam[86]	
Blood Pressure (-1)		Sphygmomanometer[48]		
Temperature (-1)		Body temp. sensor[48]	Thermal Cam	
Glucose (-1)		Glucometer sensor[48]		
WC(-1)		Dense sensing (RFID)[92]; ECM[12]; Uroflowmeter[34]; WISP[96]	Privacy Issues	Water level, heat sensors, A+RTLS
Fever/ Infection(-1)		Body temperature sensor[48]	Thermal camera	
Sweating(-1)		Galvanic skin response sensor (GCR)[48]	Thermal camera	
Shaking(-1)			Cam	A
Cough(2)		Audio-based cough detector[15]	+audio	Audio, A
Fall(2)	A^4[33]; A^T[17],[11], [57],[73],[65],[55], [16],[74],[56],[130] [137],[119]; A^B[82]; 2xA^B[23]; G[18]; AG[64]	Floor vibration-based sensor[4]; array of acoustic sensors[94]; Tilt sensor + piezoelectronic A + vibration sensor[83]; tri-axial MTx[134]; A^T+G^T[50],[127]; multiple A^T[44]; A^T+BAR[114]	Kin[72],[90]; Cam[101], [7],[41]	IR, pressure sensor, audio

Taking Medication (3)		Dense sensing (RFID)[92]; WISP[19]		
Smoking(3)		Air quality[35]; aerosol detector [115]		

It is not easy to see what the anticipated solutions for monitoring physiological signs are. Apart from the technologies listed in the *Other Sensors & Software* in Table 8 only sophisticated vision-based systems are capable of detecting most of these sub-tasks – with the exception of *Blood Pressure and Glucose*. Alternatively, intelligent garments with integrated textile electrodes and sensors could be used, yet there is lack of suitable technology and its biggest drawbacks are large energy consumption and hygiene issues (these garments would have to either be waterproof or consist of replaceable elements).

3.3.8. Meal prep., Dishwashing, Eating and Drinking

These categories of ADL are of great interest to researchers and clinicians, yet are difficult to recognise. Sub-tasks listed in Table 9, especially *Cooking and Food Preparation* involve many complex motions which differ across the whole population. People have different skills, styles, tools and preferences and hence AR involves multiple sensors e.g. heavily instrumented in sensors ambient kitchen [91] and is difficult to achieve with body-worn sensors. Proximity sensors and electricity monitoring provide alternative ways for measuring these two activities. However, solutions adopted by researchers in this space and the anticipated ones rely on heavily instrumenting the kitchen – something which is neither convenient nor easy to maintain. *Eating and Drinking*, as Table 9 suggests, are easier to recognise and have very high value in nutritional studies. Since eating and drinking is crucial to survive and has large impact on our health, a fair number of studies have addressed it already, including video-based AR. Due to this fact, there are no anticipated solutions for these two sub-tasks, as there is a wide-range of acceptable, from the user point of view, approaches already present in the literature. *Dishwashing* sub-task, whether manual or done by a dishwasher, can be detected using a single tri-axial accelerometer [85] or with the aid of RFID sensors [92]. Viable solutions include video-based AR, water metering (universal) or electricity monitoring (for dishwasher's use).

Table 9: Meal prep., Dishwashing, Eating and Drinking Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Food Preparation(3)		ambient kitchen[91]; sEMG+8xA^T[102]		Dense sensing
Cooking(3)		ECM[12]; ambient kitchen[91]		PROX, audio, gas or ECM (cooker)
Dishwashing(3)	A^T[85]	Dense sensing(RFID)[92]		Water metering, ECM (dishwasher)
Eating(3)	5xA^B[9]	Ear-attached mic.(chewing)[5]; surface EMG+mic (swallowing detection)[5]; dense sensing (RFID)[88],[92]; AGC[5],[133]; WISP[19]	Web cams[63]	
Drinking(3)	5xA^B[9]	Dense sensing (RFID)[88],[92]; AGC[5],[133]	Web cams[63]	

3.3.9. Home Management, Sleep and Work

Out of all the activities listed in Table 10, *Sleep and Work* are the most important in the context of healthy living. Sleep monitoring is something already fairly well-addressed by commercial products such as Fitbit or different smart watches. For AR of these two sub-tasks, accelerometers are again the suitable and most frequently used technology. For *Sleeping/Lying* there is a handful of alternatives e.g. pressure sensors in or under the bed or a body-worn altimeter or a tilt sensor. *Working*, if using a computer or other programmable device, can be detected via use of software apps and for other types of work video-based AR forms a good alternative. Downsides of using both these technologies have already been listed in earlier sections.

Table 10: Home Management, Sleep and Work Sub-tasks

Sub-task	On-body (accel.)	Other Sensors & Software	Video	Anticipated solutions
Open/Shut Door(2)		Door contact[95]		Dense sensing, audio
Putting Away Groceries(3)				Dense sensing

Water Plants(3)		WISP[19]		PROX, dense sensing
Using Electrical Appliance(3)		ECM[32]		Dense sensing
Sleeping/ Lying(3)	A^T[110]	WISP[19]		Pressure sensors, ALT, tilt sensor, A
Waking Up(3)				A
Working (desk, PC)(3)	A^T[131](PC), [85](PC); A^U[93](PC); 5xA^B[9]		High res. cam	SF_APPS (PC)

Home Management activities have not received much attention from the research community, which is understandable as AR of sub-tasks such as *Open/Shut Door*, *Water Plants* or *Putting Away Groceries* is of little clinical value. Yet, apart from technologies listed in Table 10, it can be accomplished with use of video cameras or dense sensing. *Using Electrical Appliance(s)* is virtually impossible to detect for a wide range of devices using accelerometers or other body-worn sensors. The most suitable, yet difficult to maintain, technology currently available is electricity monitoring or other dense sensing approaches.

4. Discussion

Is it possible for one sensor technology to discover all of the home activities with 100% accuracy? Can this sensor technology be used in both single-occupancy and multi-occupancy homes? The results of the systematic literature review presented in this paper show that an affirmative answer cannot be given for any of the reviewed sensor technologies when used on their own. Video sensors and accelerometers have the highest potential but with the current state-of-the-art they are not capable of recognising the full range of activities without even considering the practicalities of using these technologies, as they are not suited for every part of the house. Cameras would not be acceptable in areas such as bathrooms and bedrooms; for practical reasons accelerometers cannot be given to every visitor who is not living in the house. The conclusion is that currently no single sensor/sensing technology can discover all home-based ADLs. Accelerometer-based wearable sensors are promising, yet need some contextual information to differentiate between activities such as preparing tea and coffee. The solution to the problem lies in multi-modal IoT sensor systems that take into account basic principles of ubiquitous computing. It is important to design smart-spaces in such a way as to avoid over-instrumentation of both the space and subjects with redundant sensors. Fundamentally, whilst in this paper we focused only on IoT data collected in home environments, the question remains on how to establish the value of the IoT data (and, therefore, the accepted value of the IoT infrastructure required to acquire and make this data available) even before the data is used to infer some information. The SPHERE [126] project is addressing this question by carrying out quantitative evaluation of which sources of data provide best impact, according to defined metrics, on known AR algorithms.

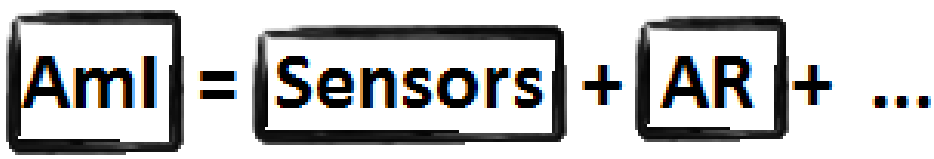

Figure 5: Ambient Intelligence.

Ambient intelligence requires input from sensors and at least some means of activity recognition – as captured in Fig. 5. Sensor systems are not very useful without AR algorithms. Some people may argue that human input is required or at least some background/contextual information about humans being monitored (age, medical conditions, habits, etc.). Some means of networking and software to run on sensor nodes is also essential, as is the semantic schema for the inferred activities. However, at minimum, sensors and AR algorithms are needed for an AmI space. Simplifying the problem down to these two elements allows focusing on relationships between these two factors. AR algorithms require sensor data as inputs, and in turn sensors produce data so that it can be reasoned over by (AR) software. Researchers in this space take one of the three approaches to make this link. For their AR algorithms they either make use of available sensor data repositories/functioning real-time sensor system, simulation software, or they need to build the sensing infrastructure as a part of their project. This poses some interesting questions, e.g. are there any specific requirements imposed by the AR algorithms or is this purely technology-driven? Does the quality of available video data drive the selection or development of video-based AR algorithms? Do some algorithms perform badly due to the low-quality of data? What is the sensitivity of AR algorithms on certain sensor data sources?

The review presented in previous section is ADL-centric and list studies in which AR succeeded via use of the named sensor technology. For loosely coupled sensor systems, data generated by sensors often drives an AR algorithms' efficiency and performance. Complex sensor systems are usually developed by a collaborative group of researchers with different specialisations. This review also informs researchers working on AR algorithms on the types of sensors they should consider in their studies for recognising particular home activities. On the other hand, it would be beneficial if this group provided information about the quality of the data required for their AR algorithms to recognise each of the home activities and on sensitivity of their algorithms on certain (sensor) data sources. Such dialogue between the two fields of research would significantly ease the development of ambient spaces and provide better justified technological support to longitudinal studies undertaken in this space. It would allow for breaking the cycle of technology-driven AR algorithm development and focusing on the scientific advancements in the field. Moreover, careful sensor selection prior to deployment would result in minimising the number of sensors while maximising the number of recognisable activities and the quality of AR. Apart from the above, other selection criteria can be applied in order to reduce cost or to mitigate privacy concerns.

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